# DECLARATION

The undersigned, Ju-young Lee, a translator working for Kasan IP & Law Firm located at 6th Fl. Youngpoong Bldg., 142 Nonhyun-dong, Gangnam-gu, Seoul 135-749, Republic of Korea, does hereby declare that he is familiar with the English language as a Korean and that the attached is a true English translation of Korean Patent Application No. 2002-0041406 (filed July 15, 2002).

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# [ABSTRACT]

[Abstract]

The present invention relates to a method of producing face description that applies general discriminant analysys (GDA) to linear discriminant analysis (LDA) components, which achieves a more accurate face-recognition rate. The final face description is produced by margining the LDA projection extracted by face elements as a single vector, and using the GDA.

[Representative Drawing]

FIG. 1

[Index Keywords]

Discriminant analysis, LDA, GDA, face elements, description

[SPECIFICATION]

[Title of the Invention]

Method of Producing Face Description by Applying GDA to LDA Projections

[Brief Description of the Drawings]

FIG. 1 illustrates the whole procedure that applies GDA to LDA components according to an embodiment of the present invention.

[Detailed Description of the Invention]

[Object of the Invention]

[Field of the Invention and Description of the Related Art]

The present invention relates to a method of producing face description that applies general discriminant analysys (GDA) to linear discriminant analysis (LDA) components, which achieves a more accurate face-recognition rate.

The GDA is an existing technology, but a more accurate face-recognition rate has been achieved when it is applied to LDA result values extracted by face elements.

[Technical Aspects to be achieved by the Invention]

An object of the present invention is to achieve a more accurate face-recognition rate by applying GDA to LDA result values extracted by face elements.

In order to achieve the object, the present invention produces the final face description by margining the LDA projection extracted by face elements as a single vector, and using the GDA.

[Embodiments and Operations of the Invention]

The present invention will be described in detail with reference to the attached drawings.

FIG. 1 illustrates the whole procedure that applies GDA to LDA components according to an embodiment of the present invention.

GDA is a method designed for non-linear feature extraction. The object of GDA is to find a non-linear transformation that maximizes the ratio between the between-class variance and the total variance of transformed data. In the linear case, maximization of the ratio between the variances is achieved via the eigenvalue decomposition similar to LDA.

The non-linear extension is performed by mapping the data from the original space $Y$ to a new high dimensional feature space $Z$ by a function $\Phi$: $Y \rightarrow Z$. The problem of high dimensionality of the new space $Z$ is avoided using a kernel function $k$: $Y \times Y \rightarrow R$. The value of the kernel function $k(y_i, y_j)$ is equal to the dot product of non-linearly mapped vectors $\Phi(y_i)$ and $\Phi(y_j)$, i.e., $k(y_i, y_j) = \Phi(y_i)^T \Phi(y_j)$, which can be evaluated efficiently without explicit mapping the data into the high dimensional space.

It is assumed that $y_{k,i}$ denotes the $i$-th training pattern of $k$-th class, $M$ is the number of classes, $N_i$ is the number of patterns in the $i$-th class, and $N = \sum_{k=1}^{M} N_k$ denotes the number of all patterns. If it is assumed that the data are centered, the total scatter matrix of the non-linearly mapped data is

$$S_T = \frac{1}{N} \sum_{k=1}^{M} \sum_{i=1}^{N_k} \Phi(y_{k,i}) \Phi(y_{k,i})^T .$$

The between-class scatter matrix of non-linearly mapped data is defined as

$$S_B = \frac{1}{N} \sum_{k=1}^{M} N_K \Phi(\mu_k) \Phi(\mu_k)^T ,$$

where $\Phi(\mu_k) = \frac{1}{N_k} \sum_{i=1}^{N_k} \Phi(y_{k,i})$.

The aim of the GDA is to find such projection vectors $w \in Z$ which maximize the ratio

$$\lambda = \frac{w^T S_B w}{w^T S_T w} \qquad (1)$$

It is well known that the vectors $w \in Z$ maximizing the ratio, such as Equation 1, can be found as the solution of the generalized eigenvalue problem

$$\lambda S_T w = S_B w \tag{2}$$

where $\lambda$ is the eigenvalue corresponding to the eigenvector $w$.

To employ the kernel functions all computations must be carried out in terms of dot products. To this end, the projection vector $w$ is expressed as a linear combination of training patterns, i.e.,

$$w = \sum_{k=1}^{M} \sum_{i=1}^{N_k} \alpha_{k,i} \Phi(y_{k,i}) \tag{3}$$

where $\alpha_{k,i}$ are some real weights. Using Equation 3, Equation 1 can be expressed as

$$\lambda = \frac{\alpha^T KWK\alpha}{\alpha^T KK\alpha} \tag{4}$$

where the vector $\alpha=(\alpha_k)$, $k=1,\ldots, M$ and $\alpha_k=(\alpha_{k,i})$, $i=1,\ldots,N_k$. The kernel matrix $K$ $(N\times N)$ is composed from the dot products of non-linearly mapped data, i.e.,

$$K=(K_{k,l})_{k=1,\ldots,M,\ l=1,\ldots,M} \tag{5}$$

where $K_{k,l} = (k(y_{k,i}, y_{l,j}))_{i=1,\ldots,N_k, j=1,\ldots N_l}$.

The matrix $W$ $(N\times N)$ is a block diagonal matrix

$$W=(W_k)_{k=1,\ldots,M} \tag{6}$$

where $k$-th matrix $W_k$ on the diagonal has all elements which are equal to $\frac{1}{N_k}$.

Solving the eigenvalue problem Equation 6 yields the coefficient vectors $\alpha$ that define the projection vectors $w \in Z$. A projection of a testing vector $y$ is computed as

$$w^T \Phi(y) = \sum_{k=1}^{M} \sum_{i=1}^{N_k} \alpha_{k,i} k(y_{k,i}, y) \tag{7}$$

As mentioned above, the training vectors are supposed to be centered in the feature space $Z$. The centered vector $\Phi(y)'$ is computed as

$$\Phi(y)' = \Phi(y) - \frac{1}{N}\sum_{k=1}^{M}\sum_{i=1}^{N_k}\Phi(y_{k,i}) \tag{8}$$

which can be done implicitly using the centered kernel matrix $K'$ (instead of $K$) since the data appears in terms of dot products only. The centered kernel matrix $K'$ is computed as

$$K' = K - \frac{1}{N}IK - \frac{1}{N}KI - \frac{1}{N^2}IKI \tag{9}$$

where matrix $I$ $(N \times N)$ has all elements equal to $1$. Similarly, a testing vector $y$ must be centered by Equation 8 before projecting by Equation 7. Application of Equations 8 and 7 to the testing vector $y$ is equivalent to using the following term for projection

$$w^T\Phi(y)' = \sum_{k=1}^{M}\sum_{i=1}^{N_k}\beta_{k,i}k(y_{k,i}, y) + b \tag{10}$$

The centered coefficients $\beta_{k,i}$ are computed as

$$\beta_{k,i} = \alpha_{k,i} - \frac{1}{N}J\alpha \tag{11}$$

and bias $b$ as

$$b = -\frac{1}{N}JKJ\alpha + \frac{1}{N^2}J\alpha JKJ \tag{12}$$

where the column vector $J$ $(N \times 1)$ has all terms equal to $1$.

The whole GDA procedure can be summarized as the following:

1. Concentrated kernel matrix $K'$ (9) (5) and matrix $W$ (6) are calculated.

2. Coefficient vector $\alpha$ is calculated by solving a generalized unique value problem (4).

3. Coefficient vector $\beta$ (11) and bias $b$ (12) are calculated.

4. The projection of vector $y$ is calculated using equation 10.

The component-based LDA face descriptor (CLFD) describes $i$th training vector $x_i$ by the LDA-projected characteristic vector set $y_i^1, y_i^2, \ldots, y_i^L$ of a certain area of a processed face $x_i$. All characteristic vectors are merged as a single vector $y_i = [y_i^1, y_i^2, \ldots, y_i^L]$, and a related characteristic vector $z_i$ is extracted using the GDA. The whole procedure is summarized as the following:

1. LDA components $y_i^1, y_i^2, \ldots, y_i^L$ for each training face $x_i$ are calculated.

2. Each face is described by merging all components as a single vector $y_i = [y_i^1, y_i^2, \ldots, y_i^L]$.

3. The GDA procedure is applied to vector $y_i$ that produces new expression $z_i$.

Refer to FIG. 1 for the description of the whole procedure.

Experiment

The suggested try has been tested in the face-modifying experiment. The MPEG and ALTKOM face database has been used for the experiment. The 5

experiments have been performed by the training and partitioning on the testing set described in Table 1.

Table 1

| | Training Set | Testing Set |
|---|---|---|
| Experiment 1<br>(MPEG) | 200 images:<br>40 persons * 5 images/1 person<br>mpeg_0066_01- mpeg_0085_05<br>mpeg_0181_01- mpeg_0200_05 | 2975 images:<br>595 persons* 5 images/1 person<br>(All image files – Training set used by version 1 descriptor) |
| Experiment 2<br>(MPEG) | 800 image:<br>160 persons * 5 images / 1 person<br>(Image field where human ID field is xxx2 or xxx4 + Training set used by version 1 descriptor) | 2375 images:<br>475 persons * 5 images /1 person<br>(All image files - Image field where human ID field is xxx2 or xxx4 - Training set used by version 1 descriptor) |
| Experiment 3<br>(MPEG) | 1685 images:<br>337 persons * 5 images/1 person<br>(Image file where human ID field is good + Training set used by version 1 descriptor) | 1490 images:<br>298 persons * 5 image /1 person<br>(Image file where human ID field is a cardinal number – Training set used by version 1 descriptor) |
| Experiment 4<br>(MPEG+ALTKOM)<br>[Training: Test =1:4] | 1035 images:<br>(Image file where human ID field is xxx1 or xxx6 + Training set used by version 1 descriptor) | 3340 images:<br>(All image files – Image file – training set used by version 1 descriptor) |

| | | |
|---|---|---|
| Experiment 5<br><br>(MPEG+ ALTKOM)<br><br>[Training: Test =1:1] | 2285 images:<br>(Image file where human ID field is good + Training set used by version 1 descriptor) | 2090 images:<br>(Image file where human ID field is a cardinal number – Training set used by version 1 descriptor) |

In special cases, each face $x_i$ is described as *5* LDA component vectors $y_i^1, y_i^2, ..., y_i^5$ and 1 LDA projection of the whole face $y_i^6$. Projection $y_i^6$ is indicated as the projection as a whole. From the merged vector *y*, 25 most important coordinates out of each component $y_i^1, y_i^2, ..., y_i^5$, and 50 most important coordinates out of the whole projection $y_i^6$ are used. In conclusion, *5×25+50=175*-dimensional vector $y_i = [y_i^1, y_i^2, ..., y_i^6]$ is obtained.

Four different faces have been compared as the following.

1. The whole descriptor face is described by 50 most important coordinates among the whole LDA projection $y_i^6$.
2. The merged descriptor face is described by *175*-dimensional merged vector $y_i = [y_i^1, y_i^2, ..., y_i^6]$.
3. The merged LDA descriptor face is described by 50 most important coordinates out of LDA projection of the merged vector $y_i = [y_i^1, y_i^2, ..., y_i^6]$.

4. The merged GDA descriptor face is described by 50 most important coordinates out of GDA projection of the merged vector $y_i = [y_i^1, y_i^2, ..., y_i^6]$.

The GDA procedure makes the use of the vast kernel function defining the linear or nonlinear characteristic extraction possible. RBF(Radial Basis Function) kernel $k(y_i, y_j) = e^{-0.5\|y_i - y_j\|^2/\sigma}$ has been used, and the kernel width is experimentally determined so that the best ANMRR rate can be produced.

In the experiment (i) ANMRR(Average Normalized Modified Recognition Rate) and (ii) FIR(False Identification Rate) for the testing set have been measured.

The Table 2 describes the result of the experiment. The result shows that the merged GDA descriptor has better performance, exempting the experiment 1. In the case of the experiment 1, the performance of the merged GDA is weak because of the over-training effect as the training set consists of only 300 faces.

Table 2

| | Experiment 1 | | Experiment 2 | | Experiment 3 | | Experiment 4 | | Experiment 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ANMRR | FIR | ANMRR | FIR | ANMRR | FIR | ANMRR | FIR | ANMRR | FIR |
| Whole | 0.1701 | 0.0666 | 0.1448 | 0.0573 | 0.1267 | 0.0477 | 0.2911 | 0.1060 | 0.1950 | 0.0641 |
| Merged | 0.1391 | 0.0491 | 0.1190 | 0.0421 | 0.1061 | 0.0336 | 0.2293 | 0.0641 | 0.1543 | 0.0373 |
| Merged-LDA | 0.3565 | 0.1983 | 0.1257 | 0.0467 | 0.0898 | 0.0222 | 0.2457 | 0.0731 | 0.1466 | 0.0368 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Merged-GDA | 0.2547 | 0.1318 | 0.1031 | 0.0358 | 0.0677 | 0.0168 | 0.2129 | 0.0545 | 0.1108 | 0.0239 |

[Effects of the Invention]

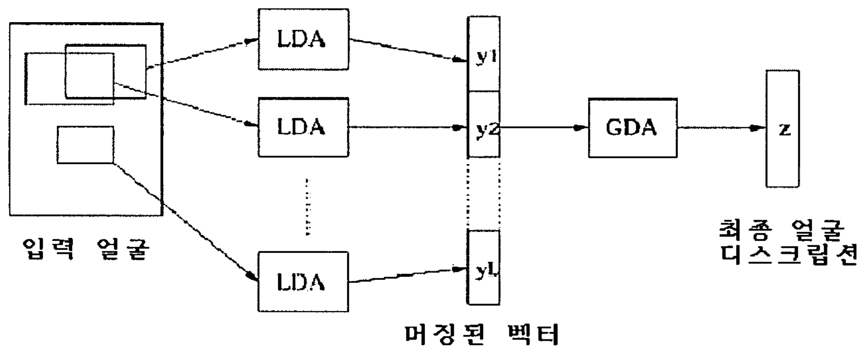
According to the present invention, a more accurate face-recognition rate can be achieved.

[Claims]

1. A method of producing a face description that applies the GDA to the LDA projection, where the LDA projection extracted by face elements is merged as a single vector, and the final face description is produced using the GDA.

Drawings

Fig 1.




Input face Merged vector Final face description